Rating Human Relations for Recommendation of an Augmented Video Memory using Human Profile Data and Meeting Logs

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Abstract

This paper presents a rating method of human relations to recommend augmented video memory using human profile data and meeting logs. To accomplish the purpose, we define categories of friends, and rating rules to show the user an augmented video memory that contains the appropriate persons. We investigated features for retrieving the videos by using a Tabletop Role-Playing Game (TRPG) style simulation.

1 Introduction

In this paper, we propose a rating method for clarifying human relations to recommend an augmented video memory, which will enable a user to recall information he/she wants to know, using human profile data and meeting logs. We termed this set of data and logs a “Dynamic Profile Network.” This work is accomplished on a wearable system for a computational augmentation of human memory. A wearer views a video of his/her interest while talking with a target person who is standing in front of him/her. Viewing this video is helpful to the person when he/she cannot recall what topic is good for the context of a conversation. Also, selecting an appropriate video from a huge video data set recorded previously is difficult for the wearer. We categorize the wearer’s friends into three types of friends. Additionally, we propose rating rules for evaluating human relations, and divide the rating rules into social rules and personal rules.

By annotating a target person’s profiles while the wearer meets the target, the wearer acquires three types of advantages: 1) recollecting the target’s profiles, 2) creating a conversation, and 3) finding candidates of the target’s new friend. These aims have been studied in wearable computing [3, 5]. However, these previous studies do not consider how the elements of human relations, i.e., personal information, should be managed. Hamasaki and Takeda also study personal networks on the WWW to find better friends [4]. Choudhury and Pentland [2] investigate human networks in the real world using the sociometer. Our study attempts to recommend video for finding better friends using the “Dynamic Profile Network” in the real world.

We conducted a Tabletop Role-Playing Game (TRPG) style simulation. The purpose of the simulation is to analyze the merits and lack of merit in our model.

2 Overview of the Nice2CU

Figure 1: Replaying a Video on the Nice2CU

We have implemented the prototype of a *Nice2CU* system for managing augmented memories by implanting them into the Dynamic Profile Network [6]. We have also proposed two operations for the Network: easy registration and automatic update. A wearer operates the system with a “Card and Mirror” interface in the real world. The system enables wearers to recall four types of a person’s information: “Profiles,” “Experiences,” “Messages,” and “Human Relations.” Figure 1 shows a scene annotating a target person’s profiles, and an automatically-recording video when the wearer met the target person on the *Nice2CU* system.

3 Rating Human Relations

In order to recommend an augmented video memory to a user, we must implement human relations in the real world into the computational world. A node corresponds to a person and a link between two nodes denotes the relationship between corresponding persons. The goal of this paper is to clarify the structure of the Network and to construct a rating pattern on the Network. We first explain the structure of the Network among recipients: a target person, the recipients’ friends, and the target’s friends. Also, we discuss what kinds of topics the recipient and the target are interested in when they meet with other persons.

• **Recipient’s friends:** First, we consider a recipient’s environment. We define a recipient’s friends as the following three types of categories (Figure 2) from

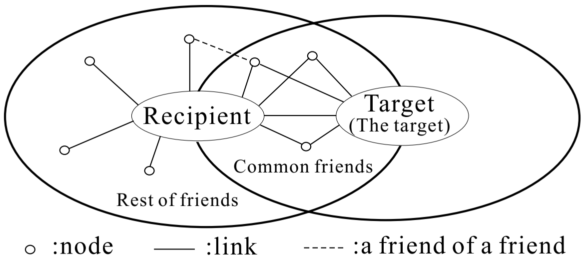

Figure 2: Set of Friends

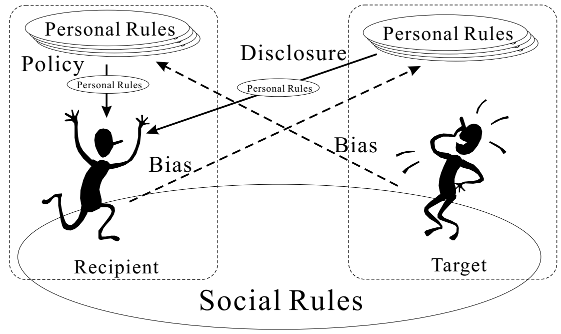

Figure 3: Two kinds of Rating Rules

the point of view of topic selection in interpersonal communication.

The Target: The target represents a person who is standing in front of the recipient. The node that corresponds to the target has been directly linked to the node of the recipient. The relationship with the target is the first step toward better interpersonal communication. The main topic of their communication is to disclose his/her self.

Common Friends: Common friends between the recipient and the target are linked directly from both nodes. If common friends between the recipient and the target exist, then these friends belong to the same community. Many people enjoy talking about news surrounding a certain common friend. This news also corresponds to the news of a certain community.

The Rest of the Friends: The rest of the friends are the recipient's friends whom the target does not know. Most of the recipient's friends are supposed to belong to this category. Taking about a person in this category gives the target a chance to find a better friend.

Second, we discuss the types of interests (rating points) in the "Dynamic Profile Network." Figure 3 depicts the kinds of rating rules in the Network. Personal rules include the recipient-side and target-side of personal rules. Here, "bias" in the figure represents the filter for deciding one's attitude to another person. Each type of rule, respectively, contains different intentions. We explain the characteristics as follows:

• **Social rules:** The aim of social rules is for users of the *Nice2CU* to pick up information of interest from another person's profiles and meeting logs. For instance, if a person is to celebrate his/her friend's birthday, we first list example patterns of social rules. Social rules cover patterns of events. In each friend type, the system individually evaluates each pattern. Social rules are representatively composed of the following five types of interests:

S1 Basic Profiles: same birthday, birthplace, affiliation, hobby, address, etc.
- *The Target and Common Friend:* Suppose that the recipient and the target were born in the same town. If they are notified of this fact, they can chat about memories in their hometown. Suppose that both the target and a certain common friend are/were once colleagues or both were once students at the same school. If this is the case, then the recipient will have a good opportunity to talk about that topic with the target.
- *The Rest of the Friends:* Suppose that the certain rest of the friends have a similar hobby about which the target is also interested. The recipient can begin talking about the topic. Also, this may be a chance for the target to find a better friend.

S2 A Friend of A Friend
- *The Rest of the Friends:* A friend of a common friend between the recipient and the target would be someone who felt more kinship than the other the rest of the friends for the target by the target. Suppose that a certain rest of friends is a friend of a certain common friend and has the same hobby in which the target is interested. The target would want to meet with the friend more than with the other rest of friends who are not friends of any common friends.

S3 Messages
- *The Target:* Suppose that the recipient has borrowed a small amount of money from the target. If the recipient meets the target, the recipient can pay back the debt to him/her immediately by viewing the video message.

S4 Unbalanced Meeting
- *Common Friends:* Suppose that the recipient meets with a certain common friend more frequently than the target does. The target can request that friend to send a message such as: "I miss you. Please, call me," to the recipient.

S5 Temporal Events
- *The Target and Common Friends:* Suppose that a certain friend's birthday will be in a few days. The recipient and the target could plan to celebrate this certain friend's birthday. Also, suppose that the winter vacation is approaching and, the recipient, the target, and some of the common friends enjoy the same hobby of winter sports, e.g., skiing and snowboarding, then they can plan to go to a winter sports resort together.

• **Personal rules:** The recipients can also adopt their own attitude to the person they are meeting. Social rules cannot represent these kinds of personal properties. Such social rules are composed of the recipient-side of personal rules and the target-side of personal rules. The recipient-side rules are used to modify a recipient policy to the target. For instance, the recipient changes his/her own attitudes when he/she meets with his/her parents, teachers, or friends. The target-side of personal rules represent the desire of what topics he/she wants to be talked about by the recipient. For example, the target can set the following personal rule, "If a certain rest of friend is a different sex from the target and is younger/elder than him/her, then the rating of videos recording the friend should be improved by 100 points," if he/she wants to get a new girl/boy friend. Most of personal rules have complementary and adaptive roles. However, personal rules additionally have another important role. A person sometimes wants to have a completely different type of meeting with someone. The following "Anti-patterning" section provides several types of possible meetings.

Anti-Patterning: Anti-patterning represents the reverse of previously defined rules. For instance, "If a certain recipient's friend has different hobbies, then the rating of videos recording the friend should be improved by 15 points" is an example of anti-patterned rule when social rules include "If a certain rest of friends and the target have the same hobby, then the rating of videos recording the friend should be improved by 15 points" as one of rules. The *Nice2CU* system also computes an entire inversive evaluation in a certain anti-patterned rule. This anti-patterning allows for a high complexity of human networks. A complex human network leads to changes in dramatically clustered communities.

• **Properties for Accessing Data:** In this paper, the *Nice2CU* system is allowed to rate human relations using the entire data of the target, the rest of the friends, the recipient's common friends, and the target's common friends. The data of the target's common friends are sent to the recipient's system. However, the data of the target's rest of friends are not allowed to be sent to the recipient's system because of privacy.

• **Rating Function:** Rating scores are computed in equation (1) in this paper. Note that, x_i is the point on the i-th rule, and w_i is a weighted factor on the i-th rule. N is a number of the rules.

$$Score = \sqrt{\frac{\sum_{i=0}^{n} w_i x_i^2}{N}} \tag{1}$$

4 Experiments

We have conducted a verification of the proposed idea using a Tabletop Role-Playing Game (TRPG) style experiment. We have employed a simulator imitating the world where all wearers use the *Nice2CU* system. We employed the simulator so that we can fundamentally correspond the verification of the rating method in the virtual world to verification in the real world, without an evaluation of user interfaces.

4.1 Methods

Three test subjects (players) participated in the experiment. Twelve characters were prepared, and the human network depicted in Figure 4 (left) was prepared in advance. Although real profiles are employed in the network, human relations are assumed virtually by the experimenter. All nodes in the figure are set character's profiles. Relationships of a certain kind between two characters (node) are represented as a link in the figure. Each player acted as four characters. The period of the TRPG was eight-months virtually. The simulator can control all meeting of the events, and can select a recipient person and a target person. The simulator can register a target person as a new recipient's friend when he/she meets virtually with the target. In the experiment, the simulator recorded all the character's actions.

4.2 Results

Table 1: Pattern of Video Replay Times

Times	0	1	2	3	4	5	6
Amount	107	122	51	14	9	1	1

In this simulation, the simulator shows scenes 305 times to the players as a total number of recommendations. Table 1 shows the number of times each video was replayed. 35% of recorded videos were not replayed in the simulation. Characters totally left 20 messages to other characters, and 17 of 20 messages were replayed. There were 15 first meetings. The average number of replayed videos of a character was 25.67, and the standard deviation was 13.52.

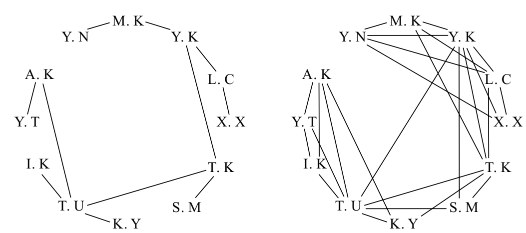

Figure 4: Initial and Simulated Human Networks

Figure 4 (right) shows the network at the end of the simulation. The average number of links in a node was 4.33, and the standard deviation was 1.56. Note that, the initial average number of links in a node was 1.83, and that the standard deviation was 1.03.

Table 2: Ranking Ratio

Rank	1-5	6-10	11-15	16-20
L.C	0.69	0.19	0.13	0.00
Y.K	0.61	0.24	0.15	0.00
T.K	0.56	0.19	0.10	0.15
Y.N	0.53	0.33	0.13	0.00
X.X	0.50	0.29	0.21	0.00
T.U	0.49	0.11	0.16	0.24
Y.T	0.43	0.36	0.21	0.00
I.K	0.40	0.35	0.20	0.05
S.M	0.40	0.25	0.15	0.20
A.K	0.40	0.03	0.30	0.27
K.Y	0.38	0.19	0.24	0.19
M.K	0.36	0.41	0.14	0.09
Avg	0.49	0.21	0.17	0.13

Table 2 shows the average of the replayed ranking ratio of recommended and replayed videos in the recommended top 20 videos. 49% of the top 1-5 ranked videos were selected in the simulation. 30% of the top 11-20 ranked videos were selected. The results show that the quality of the recommendations becomes unstable.

Table 3 shows the number of selected videos in each rank. We also categorize each meeting event in the simulation into the following three types: (1) Meeting,

Table 3: Selection Patterns of Video Rankings

Ranking		1-5	6-10	11-15	16-20
Meeting		82	48	38	31
	(ratio)	0.41	0.24	0.19	0.16
Paperwork		12	5	8	3
	(ratio)	0.43	0.18	0.29	0.11
General	Toral	60	15	7	7
	(ratio)	0.67	0.17	0.08	0.08
	Amusement	5	1	3	1
	Birthday	7	0	0	0
	Dinner	21	5	1	4
	Greeting	3	1	0	1
	News	7	1	0	0
	Sports	13	4	2	1
	Trips	4	3	1	0

Table 4: M and SD of Rank of Replayed Videos

		M	SD
Meeting		8.15	6.87
Paperwork		8.14	6.19
General	Total	5.07	7.15
	Amusement	7.30	7.60
	Birthday	2.86	1.36
	Dinner	5.45	7.71
	Greeting	7.00	7.71
	News	2.38	2.98
	Sports	4.60	8.58
	Trips	5.38	3.06

(2) Paperwork, and (3) General. To further investigate the simulation, we discriminate a general category among "Dinner," "Sports," "Birthday," "News," "Trips," and "Greetings." Table 4 shows the averages (M) and the standard deviations (SD) of the rank of the replayed videos.

Figure 5 shows replayed 17 message videos in the 20 left messages. All players chose a message when it showed in a cartain ranking at first time.

4.3 Discussions

The most useful social rule is the S3(Messages) condition. In Table 5, 88.2% of S3 videos were selected when the videos showed the 1st rank. The message was used when a character had been on either a business trip or a sightseeing trip in the simulation. In the S5(Temporal Events) condition, for instance, a certain friend's birthday will be in a few days, and all videos showed within 1-5 ranks. This condition also gave a character the opportunity for a current conversation with a friend, and for a discussion about a future plan to meet the friend another day. Table 3 and 4 also show the performance of the model. However, Birthday and News in Table 4 represent low M and SD (Birthday M:2.86, SD:1.36; News M:2.38, SD:2.98). In contrast, Meeting and Paperwork showed a high ratio of the 16-20 ranks in Table 3, and M and SD (Meeting M:8.15, SD:6.87; Paperwork M:8.14, SD:6.19) were also high in Table 4. We believe that the model has the merit of recommendating video containing temporal contexts as in the S5 condition.

This work has the shortcoming of not providing an opportunity to find better friends using the *Nice2CU*, as shown in Figure 4. Human networks are constructed under a rule termed "scale-free networks" [1] in our "small-world" [7]. The scale-free network, however, does not provide balanced opportunities among

Table 5: Ranking Patterns of Message

Rank		1	2	3	4
Meeting		10	0	0	1
General	Amusement	2	1	0	0
	Dinner	1	0	0	0
	Trips	1	0	0	0

people who are referred to as the so-called "rich who just get richer." In terms of our model, it means a "rech person" represents a person who has more and more friends. In the simulation, we found that characters who had fewer friends had less chance to connect with other friends (Figure 4, initial SD: 1.03, final SD: 1.56) It is important for the characters to have an equal opportunity to make a friend even if the quality of information for their everyday lives would be low for the "rich." We believe that this service finally gives the user a good quality of information.

5 Concluding Remarks

In this paper, we proposed a human relations-based rating method to recommend augmented video memory using a user's profile data and meeting logs. We first structuralized the "Dynamic Profile Net." We then defined two types of rating rules and proved the characteristics. Also, we showed the rating policy and the rating functions. Finally, we conducted the TRPG style simulation to prove the proposed rating model. The following three research topics are in preparation for future work.

1. Generalization: analyzing rating patterns
2. Satisfaction: improving a rating function
3. Facilitation: developing a rating rule script

An additional issue to be addressed in our work regarding the *Nice2CU* is to provide a stabilized system for rating human relations in the real world. This issue, when settled, would be employed to investigate the usability of a video recommendation interface.

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